EAI Endorsed Transactions
on Tourism, Technology and Intelligence

Review Article EAI.EU

Overview of Quantum Machine Learning for 6G

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Abstract

The forthcoming sixth generation (6G) of wireless networks requires fundamental rethinking of network intelligence, driven by the transition toward ubiquitous cognitive networks and the unprecedented complexity beyond 5G. The optimization demands of 6G surpass the capabilities of classical heuristics and conventional Machine Learning (ML), which encounter significant limitations in addressing dimensionality challenges in ultra-massive multiple-input multiple-output/terahertz/reconfigurable intelligent surfaces-assisted systems, stringent sub-millisecond latency requirements, and severe energy bottlenecks at the edge. Motivated by these gaps, this review investigates Quantum Machine Learning (QML) as a transformative solution, merging quantum mechanics with data-driven intelligence. We propose a unified and forward-looking perspective on ML integration for 6G, bridging previously siloed research domains such as cross-layer optimization, semantic- and intent-driven communication, and quantum-inspired acceleration. Furthermore, this work systematically reviews quantum-enhanced optimization methods and analyzes QML's role as an intelligence anchor, demonstrating its potential to provide context-aware, resilient, and sustainable network control across various layers. Ultimately, the paper outlines pathways for integrating QML to ensure timely, scalable, and secure decision-making in the volatile 6G landscape.

Received on 06 September 2025; accepted on 18 November 2025; published on 20 November 2025

Keywords: Quantum Machine Learning, 6G

doi:10.4108/eettti.10497

1. Introduction

1.1. Background on 6G Evolution

The sixth generation of cellular networks (6G) represents more than just an incremental leap over its predecessor (5G) [1–3]. It signals a paradigm shift toward networks that are intelligent, immersive, and symbiotic with human, machine, and environmental systems. While the fifth generation of cellular networks (5G) introduced Enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communication (URLLC) [4], Space-Air-Ground Integrated Network (SAGIN) [5, 6], and Massive Machine Type Communications (mMTC), its design was still anchored in throughput-centric optimization [7]. Unlike 5G, 6G envisions *ubiquitous cognitive* networks that are context-aware and seamlessly integrate physical, digital, and biological domains [8].

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The vision involves extensive connectivity, expanding from billions of devices to trillions of interactions across land, air, sea, and space infrastructures. 6G is designed to orchestrate not only communications but also intelligence [9] and sensing [10]. This ensures that every interaction, whether among machines, humans, or hybrid systems is meaningful, timely, and sustainable. Key enablers include:

1. *Holographic, Extended Reality (XR) Communications and Real-time Sensory Interaction*: Delivering photorealistic holographic conferencing and mixed-reality experiences serves multiple purposes, including remote collaboration, medical training, immersive education, and entertainment [11]. These applications require real-time synchronization across edge and core networks [12].

2. *Semantic Communications*: Shifting from bit transmission to meaning transmission ensures that

only decision-relevant or context-rich information is exchanged [13]. This approach reduces bandwidth consumption and enhances efficiency under congestion.

3. *AI-Native Networks*: positioning Artificial Intelligence (AI) not as an add-on but as an intrinsic fabric of the network [14, 15]. Predictive analytics, adaptive resource optimization, and proactive self-healing mechanisms are embedded directly into the control plane [16].

4. *Integration of Non-Terrestrial Networks (NTNs)*: Enabling resilient, global coverage holds significant importance [17]. This is achieved by unifying terrestrial networks with satellite constellations, unmanned aerial vehicle (UAV) relays, and maritime links [18, 19]. Such integration ensures uninterrupted services during natural disasters or in under-served regions.

5. *Ubiquitous Intelligence and Digital Twins (DT)*: Creating a virtual replica of network entities and services is essential. These DTs are continuously synchronized with physical systems [20]. This synchronization allows for the forecasting of behavior, conducting what-if analyses, and supporting proactive orchestration of resources [21].

Fig. 1 illustrates the background and evolution of 6G connectivity.

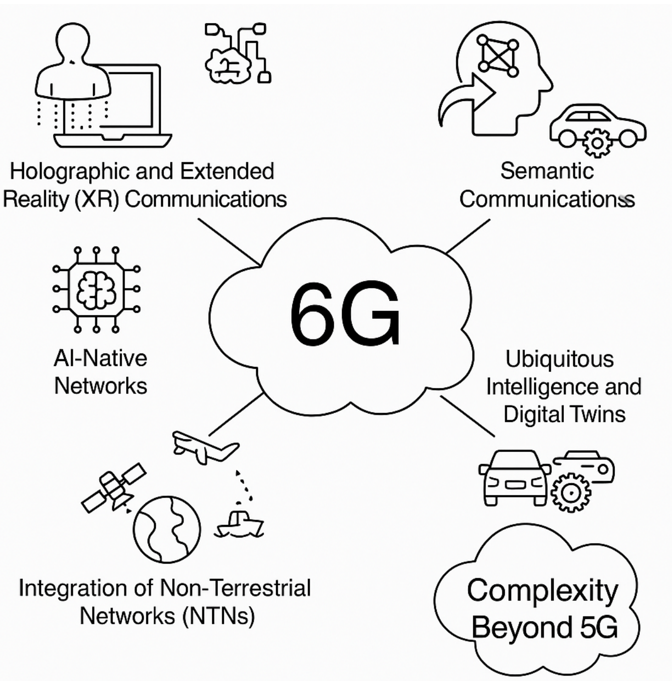

Figure 1. The 6G networks and evolutions

1.2. Complexity Beyond 5G

The transition from 5G, which concentrated on enhanced broadband, low-latency, and Internet-of-Things (IoT) connectivity, to 6G significantly increases system complexity [22]. It aims to intelligently unify diverse devices, services, and infrastructures [23]. This complexity stems from distinct devices, limited spectrum, varied services, sustainability demands, and real-time adaptability needs [24]. Multi-dimensional applications now require higher data rates along with sub-millisecond latency, near-perfect reliability, semantic-aware delivery, and carbon-efficient operation [25]. These requirements interact in non-linear ways across devices, spectrum, and services, creating optimization landscapes that are too complex for classical heuristics.

The complexity of heterogeneity, scarcity, and strict Quality of Service (QoS) demands in 6G necessitates shifting from traditional methods [26]. AI-native, semantic-driven, and quantum-accelerated learning frameworks are essential for scalability, adaptability, and sustainability [27]. The complexity beyond 5G involves a fundamental shift to multi-objective, cross-layer, and context-driven orchestration. This requires rethinking network intelligence, moving from static and offline models to dynamic, hybrid, and quantum-enhanced learning frameworks suited for the volatile, mission-critical 6G landscape [28].

1.3. ML-Integrated 6G Enabling

Machine Learning (ML) remains indispensable for 6G when deployed as a cross-layer enabler, but it must evolve beyond today's paradigms. Integration must be deliberate, systematic, and matched to each layer's unique constraints.

1. *Physical (PHY) Layer*: ML can refine channel estimation under sparse Terahertz (THz) propagation, optimize beamforming with Reconfigurable Intelligent Surfaces (RIS), and jointly design sensing and communication waveforms [29, 30]. These tasks benefit from continual adaptation, where models evolve with channel conditions rather than relying on static training.

2. *Media Access Control (MAC) and Network (NET) Layers*: Dynamic scheduling, admission control, and slicing can be enhanced through Deep Reinforcement Learning (DRL) [31]. Yet these must account for non-stationarity, safety constraints, and fairness. Federated learning enables distributed intelligence while safeguarding data sovereignty, but it must address the heterogeneity of clients and network conditions [32].

3. *Application (APP) Layer*: Semantic encoders/decoders shift communication

toward conveying task-relevant knowledge [33]. Transformers and Graph Neural Networks (GNNs) anticipate user demand, proactively cache content, and enable predictive analytics [34]. For XR and holography, adaptive learning optimizes resolution and motion prediction, preserving immersion even under fluctuating bandwidth.

Architectural Imperatives. The architecture must incorporate lifelong learning to avoid catastrophic forgetting, meta-learning for rapid adaptation, and self-supervised approaches to thrive in sparse-label environments. Critically, learning must occur across timescales: heavy model selection in the core, policy adaptation at the edge, and deterministic inference at devices. This decomposition ensures predictability while retaining adaptability.

1.4. Limitations of Classical ML in the 6G Context

Recent studies have explored ML-driven approaches in 6G, addressing challenges in scalability, efficiency, adaptability, and security.

1. *Scalability and Dimensionality*: The integration of Ultra-massive Multiple-input Multiple-output (MIMO), RIS-assisted channels, Integrated Sensing and Communication (ISAC), and large of IoT devices in 6G demands solutions that can process astronomical state spaces [35, 36]. Classical ML models, reliant on large datasets and deep architectures, scale poorly in energy and latency [37, 38].

2. *Real-Time Constraints*: Sub-millisecond deadlines in extended URLLC (xURLLC) and internet applications cannot tolerate the multi-millisecond inference cycles typical of Deep Learning (DL) models [39]. This issue is particularly pronounced under fast-varying conditions such as high-mobility vehicular networks [40].

3. *Energy and Resource Bottlenecks*: Edge devices, from UAVs to medical wearables, operate under severe energy budgets [41]. Running large neural models drains batteries, accelerates hardware degradation, and threatens sustainability goals.

4. *Generalization in Dynamic Environments*: Classical models trained offline often fail when confronted with rapidly evolving traffic, mobility, or spectrum availability [42]. Retraining pipelines are too slow to ensure adaptive performance.

5. *Multi-Agent Coordination*: Distributed reinforcement learning for multi-agent systems struggles with exponential growth in joint action spaces [4, 31, 43]. Coordination under partial observability and constrained bandwidth becomes infeasible with classical methods.

6. *Security and Trust*: Adversarial attacks, data poisoning, and privacy breaches are magnified in 6G's heterogeneous and decentralized deployments [44]. Centralized training pipelines expose sensitive user data, while Federated Learning (FL) models remain vulnerable to gradient leakage.

These limitations underscore that while classical ML remains foundational, it cannot alone satisfy 6G's aspirations. The inability to guarantee timely, scalable, energy-efficient, and secure decision-making motivates the search for novel approaches that blend classical, quantum, and semantic paradigms.

Despite recent advances, classical ML methods face challenges with 6G demands in computational efficiency, optimization speed, handling high-dimensional data, privacy, and scalability in dense networks as noted in [37, 38, 45–47]. These challenges motivate research to enhance ML for advanced wireless networks. Quantum Machine Learning (QML) can address these bottlenecks by leveraging quantum features for faster optimization, better generalization, and real-time decision-making, thus advancing network intelligence in 6G.

Table 1 lays out limitation of classical ML approaches and corresponding QML solutions.

1.5. Why QML for 6G

QML evolves machine learning by merging quantum mechanics with data-driven intelligence to tackle 6G network complexity [48]. Unlike classical models limited by sequential processing and resource constraints, QML uses superposition, entanglement, and quantum parallelism for faster optimization, enhanced feature extraction, and scalable adaptation in 6G environments [53]. Parameterized Quantum Circuits (PQCs), where tunable parameters are embedded into quantum states through quantum gates, form the backbone of QML architectures, enabling flexible training, generalization, and integration into hybrid systems.

QML's potential for 6G hinges on its ability to operate under ultra-low latency, massive connectivity, and heterogeneity. By encoding data into quantum states, QML can evaluate an exponential number of possibilities simultaneously, exceeding classical ML capabilities. This is crucial for 6G's needs in real-time decisions, dynamic orchestration, and reliable adaptation.

1. *Quantum Parallelism for Accelerated Model Training*: Quantum parallelism enables quantum processors to evaluate many parameter configurations at once [54]. This reduces convergence times and improves response in 6G applications like

Table 1. Limitations of Classical ML and Corresponding QML Solutions

Category	Limitation	Implication	QML Solution
Scalability	Curse of dimensionality in massive MIMO/THz/RIS [29, 35]	Large datasets and heavy compute strain edge devices	Quantum kernels and QSVMs handle high-dimensional data efficiently [48]
Latency	Deep Neural Network (DNN) inference exceeds sub-ms limits [49]	Fails in URLLC and mobility-sensitive tasks [25]	VQCs and QRL exploit quantum parallelism for faster decisions [50]
Energy	High computational and memory resources needed at the edge	Battery drain and unsustainable IoT operation [51]	Hybrid quantum–classical models offload intensive tasks [52]
Generalization	Poor adaptability to non-stationary environments	Frequent retraining and degraded QoS	Quantum transfer learning and re-uploading enhance adaptability
Multi-Agent	Multi-Agent RL (MARL) scales poorly with many agents [32]	Limited coordination in UAV swarms and SAGIN [6]	Quantum-inspired ML uses entanglement for scalable cooperation
Security	Vulnerable to adversarial attacks and leakage [44]	Risks to trust, reliability, and compliance	QML with QKD and quantum randomization improves resilience and privacy

beamforming optimization and UAV scheduling. It allows faster adaptation to changing wireless environments and supports near real-time learning where classical ML models falter [55].

2. *Exponential Speedups in Optimization and Feature Extraction*: Many 6G challenges are combinatorial, like channel assignment, SAGIN network routing, or slice resource allocation among service classes. Quantum Approximate Optimization Algorithm (QAOA) and Variational Quantum Eigensolvers (VQEs) offer near-optimal solutions with polynomial resource scaling, surpassing classical heuristics [56]. Quantum kernel methods and Quantum Support Vector Machines (QSVMs) enhance data separability and classification accuracy for interference detection, mobility prediction, and anomaly recognition by mapping data into high-dimensional Hilbert spaces. This quantum advantage allows for more robust and efficient feature extraction than classical models [57].

3. *Seamless Integration with Federated and Edge Intelligence*: The hybrid quantum-classical paradigm allows quantum and classical components to share tasks. Quantum processors handle compute-heavy tasks like feature mapping and policy search, while classical modules handle latency-sensitive inference [58]. In federated learning, quantum nodes offer encrypted gradients or efficient parameter updates, enhancing privacy and efficiency. This integration fits QML into 6G's distributed structure, boosting capabilities without disrupting operations.

4. *Enhanced Robustness, Privacy, and Security*: Beyond optimization, QML boosts the trustworthiness of 6G systems. Quantum cryptography like Quantum Key Distribution (QKD) can secure federated QML pipelines while PQC-based anomaly detectors defend against adversarial attacks in spectrum sensing or semantic communication [59]. Learning with quantum randomness improves resilience to data poisoning, model inversion, and gradient leakage attacks, ensuring privacy in decentralized 6G ecosystems.

5. *Pathway to Sustainable and Carbon-Aware Intelligence*: Training large classical ML models requires significant energy, but QML circuits offer more energy-efficient solutions by decreasing computational depth and utilizing quantum accelerations [60]. In 6G networks, where sustainability is vital, QML can strategically offload tasks to quantum processors, aligning quantum jobs with renewable energy periods through green scheduling policies [61]. Thus, QML enhances performance and promotes sustainability for future networks.

QML tackles key 6G ML challenges, such as scalability, latency, adaptability, and security, by introducing a new computational model. Integrating QML into 6G allows networks to proactively learn and optimize, providing not just connectivity, but also context-aware, resilient, and sustainable intelligence.

Table 2 summarizes limitation of Classical ML and QML-relevant ML studies for 6G Networks.

1.6. Motivation and Contributions for Rethinking Network Intelligence

Motivation. The motivation for this study stems from the unmatched complexity of 6G networks. These networks must support ultra-reliable, low-latency services, orchestrate billions of heterogeneous devices, and integrate terrestrial, aerial, maritime, and orbital infrastructures under strict energy and sustainability constraints [51]. Classical ML methods, though effective in 5G, face clear limits in scalability, adaptability, and trust, making them insufficient for the demands of 6G. This raises a critical need for new paradigms of intelligence that can deliver secure, scalable, and proactive network control. This study presents an integrated framework combining machine learning and quantum-inspired optimization, critical for 6G networks. Unlike previous surveys treating them separately, it offers a unified approach and a blueprint for developing 6G as an intelligent, sustainable, and human-centric network.

Technical Contributions. This study advances the state of knowledge by offering a unified and forward-looking perspective on the role of ML in enabling 6G networks, bridging three research domains that have often remained siloed: cross-layer optimization, semantic- and intent-driven communication, and quantum-inspired acceleration. Beyond consolidating recent advances, the study systematically identifies architectural gaps and formulates an integrative ML-driven framework tailored for scalability, adaptability, trust, and sustainability in next-generation wireless systems. The key technical contributions are outlined below:

1. *Unified ML-Integrated 6G Framework*: We present a comprehensive synthesis of classical ML, semantic-aware learning, and quantum-inspired methods as a unified paradigm for 6G. This framework explicitly addresses the limitations of classical approaches by incorporating adaptability, energy efficiency, and robust decision-making across timescales and network layers.

2. *Taxonomy of Cross-Layer Architectures*: We propose a structured classification of ML integration across physical, MAC, network, and application layers, spanning device–edge–cloud continuum. Each category is analyzed in terms of scalability, latency, privacy, energy efficiency, and sustainability, providing a reference blueprint for selecting deployment strategies under diverse service requirements.

3. *Survey of Quantum-Enhanced Optimization Methods*: We comprehensively review advances in quantum-inspired and quantum-enabled algorithms. Their applicability to 6G challenges in real-world scenarios are assessed with respect to scalability, solution quality, and real-time feasibility.

4. *Integration of QML*: We investigate how QML can act as intelligence anchors for 6G, supporting optimization and seamless integration between physical and virtual entities. The study highlights how QML-enabled enhances processing speed and resilience against uncertainties, while also providing a safe testbed for deploying ML-driven and quantum-accelerated policies.

2. Fundamentals of QML for 6G

2.1. QML Paradigm Layers

QML for 6G is a multi-layered system where quantum foundations, machine learning methodologies, and hybrid orchestration mechanisms interact [68]. The quantum layer introduces computational elements, such as quantum superposition, quantum entanglement, and quantum interference to naturally handle 6G optimization's complex and high-dimensional tasks. Classical ML methods are essential for managing large datasets, preprocessing, and feature extraction [69]. The hybrid orchestration layer coordinates quantum subroutines to enhance classical pipelines. Mapping these layers onto the 6G stack reveals clear synergies:

- *PHY layer*: quantum-enhanced classification for channel estimation and detection [69].
- *MAC layer*: QRL-driven scheduling for adaptive resource allocation.
- *NET layer*: quantum-inspired routing and slicing under latency and energy constraints.
- *APP layer*: quantum semantic encoders for holographic and XR communications [70].

QML in 6G complements classical ML by accelerating tasks facing scalability, latency, or energy limits.

2.2. Quantum Layer

The quantum layer forms the foundation of QML, introducing capabilities that extend beyond classical computing. Key principles include:

- *Quantum Superposition*: enabling parallel exploration of many states, ideal for channel state search or RIS phase optimization [71].

Table 2. Comparative Analysis of QML-Relevant ML Studies for 6G Networks

Study	Core Focus	Contribution	Key Limitation	QML Relevance
[37]	ML challenges in 6G	Identifies issues in scalability, adaptability, efficiency, and security	Computational inefficiency and limited adaptability for real-time tasks	QML offers faster training, scalability in high dimensions, and improved adaptability
[38]	Large-scale optimization	Hybrid model-/data-driven ML for resource allocation, scheduling, and interference management	High computation and retraining overhead for dense networks	QML accelerates optimization for combinatorial tasks and reduces training cost
[45]	Privacy in ML for 6G	Explores FL and differential privacy for bandwidth-limited environments	Vulnerability to leakage and heavy communication overhead	Quantum-secure FL enhances privacy with reduced data exposure
[62]	Trends and applications of ML in 5G/6G networks	Discusses mobility management, resource optimization, and intelligent service provisioning	Lacks concrete frameworks for scalability in heterogeneous networks	QML frameworks enable scalable orchestration across diverse services
[63]	AI/ML for 6G IoT	Reviews supervised, unsupervised, and RL for IoT device management and security	Limited real-time adaptability for constrained IoT devices	Lightweight QML models provide efficiency and resilience for IoT nodes
[64]	ML roles in ISAC for 6G	Identifies ML for channel estimation, detection, and waveform optimization	Struggles with accuracy under dynamic conditions	QML kernels improve estimation and feature extraction in ISAC
[46]	ML-powered 6G networks	Summarizes automation, self-healing, and spectrum intelligence	Lacks scalability for ultra-dense networks	QML scales decision-making and enhances self-optimization
[47]	ML for 6G URLLC enhancement	Examines adaptive ML for reliability and latency reduction	Inability to meet sub-ms demands under dynamic load	QRL enables ultra-fast decision-making and predictive reliability
[65]	ML-driven RRM	Highlights ML for resource management, slicing, and security	Computational complexity and lack of standardization	QML enhances scalable RRM and integrates with evolving standards
[66]	AI/ML for 5G/6G	Provides AI integration model with 6G extensions	Limited applicability to emerging 6G services	QML extends scalability and adaptability to future 6G applications
[67]	ML-based waveform design	Proposes adaptive ML framework for waveform management	High complexity in dynamic spectrum environments	QML circuits optimize waveform selection with lower overhead

- *Quantum Entanglement*: offering non-local correlations that can model interactions across devices in ultra-dense networks.
- *Quantum kernels*: projecting data into high-dimensional Hilbert spaces where linear separability is improved [72].

Algorithms such as the QAOA, VQE, and Grover's search become particularly relevant for solving 6G problems in beam selection, user association, and routing [73]. QSVMs and quantum kernel methods can enhance feature discrimination in channel prediction and interference classification. The quantum layer is limited by current hardware challenges, such as low qubit counts and high error rates, which makes Noisy Intermediate-Scale Quantum (NISQ) systems the primary focus of near-term QML research, relying on shallow circuits, error mitigation, and classical–quantum hybrid approaches.

2.3. Classical ML Layer

Although quantum techniques hold promise, classical ML is essential. In 6G, ML models like Deep Neural Networks (DNNs), Reinforcement Learning (RL), and transfer/meta-learning excel in data-heavy tasks [65]. These include traffic forecasting, user profiling, and slice orchestration [74]. This is due to their scalability and established training pipelines.

However, classical ML struggles with:

- *Latency*: inference delays conflict with sub-millisecond xURLLC requirements [4, 23].
- *Adaptability*: catastrophic forgetting and retraining costs in dynamic, non-stationary 6G environments [75].
- *Energy efficiency*: massive compute loads at the edge lead to unsustainable energy consumption.

Classical ML serves as the foundational layer, with quantum algorithms acting as specialized accelerators.

2.4. Hybrid Quantum-Classical Intelligence

Hybrid quantum-classical intelligence is the most practical pathway for QML in 6G [76]. Rather than relying solely on immature quantum hardware, hybrid systems integrate classical and quantum modules in complementary roles. For example:

- *Classical front-end*: preprocessing, dimensionality reduction, and handling of large-volume sensor data.
- *Quantum back-end*: kernel lifting, combinatorial optimization, and policy search where quantum parallelism provides an edge [77].

Deployment models span:

- *Non-Real-Time (Non-RT)* cloud analytics, where complex QML models are trained offline.
- *Near-Real-Time (Near-RT)* RAN Intelligent Controller (RIC) environments, where shallow PQCs refine policies under dynamic conditions.
- *Edge* systems, where lightweight Quantum-Inspired Machine Learning (QiML) heuristics provide fast, energy-efficient approximations.

Hybrid frameworks can employ quantum budget policies to dynamically determine when to use quantum subroutines based on task urgency, energy availability, and risk [78]. This optimizes the efficient and sustainable use of quantum resources.

Table 3 compares layer of Classical ML, Quantum ML, and Hybrid Quantum–Classical ML.

2.5. Tri-Layer QML Orchestration

The orchestration of quantum, classical, and hybrid intelligence layers is vital for 6G operation [79]. Tri-layer orchestration ensures that tasks are dynamically allocated to the most appropriate intelligence layer:

- *Quantum-only execution* for tasks requiring high-dimensional feature discrimination or combinatorial optimization [80].
- *Classical-only execution* for routine, data-heavy processes with well-established ML pipelines.
- *Hybrid execution* for cross-layer tasks, where classical preprocessing and quantum optimization interact.

Orchestration is guided by latency, energy, and Service-Level Agreement (SLA) constraints. In vehicular SAGIN scenarios, routine location updates might use classical ML, while real-time handovers and resource allocation during high mobility could utilize Quantum Reinforcement Learning (QRL) policies.

2.6. Synergies in QML Frameworks

The true value of QML emerges from synergistic frameworks where quantum and classical intelligence amplify each other [81]. Some examples include:

- *PHY classification*: QSVMs outperform deep neural classifiers for high-dimensional THz channel estimation.
- *MAC scheduling*: QRL offers faster convergence in multi-agent scheduling under bursty traffic.
- *NET routing*: QAOA finds low-latency, energy-efficient routes in ultra-dense IoT topologies.
- *APP layer semantics*: quantum semantic encoders compress and transmit meaning, improving spectral efficiency [48].

Synergy evaluation metrics now include semantic fidelity, fairness, carbon footprint, and resistance to adversarial attacks, shifting the focus from performance to overall network intelligence.

2.7. Toward Trustworthy and Sustainable QML for 6G

Trust and sustainability are becoming first-class objectives in 6G. For QML, this implies:

- *Explainability and trustworthiness*: ensuring QML decisions are auditable, especially in safety-critical applications like autonomous driving or telesurgery [82].

Table 3. Comparison of Classical ML, Quantum ML, and Hybrid Quantum–Classical ML for 6G

Layer	Key Capabilities	Role in 6G	Strengths	Limitations
Classical ML	Deep nets, RL	Data handling & feature extraction	Scalable & mature	Latency & energy issues
Quantum ML	Superposition, entanglement, quantum kernels	Combinatorial & high-dim tasks	Parallelism & improved separability	NISQ hardware constraints
Hybrid Quantum–Classical	Mix of classical and quantum modules	Coordinated hybrid pipelines	Leverages strengths of both paradigms	Integration complexity & variable benefits

- *Sustainability focus*: carbon-aware orchestration of quantum workloads, scheduling QPU-intensive tasks during green-energy windows.
- *Governance frameworks*: defining Quantum Service-Level Agreements (Q-SLAs) that include quantum-specific metrics (shot budgets, queue delays, error rates).

QML could anchor green AI in telecommunications, promoting efficient communication and sustainable operations aligned with climate goals.

2.8. Cross-Domain Applications of QML in 6G

QML is not confined to any single service category; its cross-domain potential is transformative [83]. Example applications include:

- *Autonomous mobility*: Quantum Proximal Policy Optimization (Q-PPO) for SAGIN vehicles to optimize semantic caching, routing, and safety-critical decisions [5, 81].
- *Industry 5.0*: QML-enhanced predictive maintenance, adaptive robotics, and resilient factory networks [84].
- *Immersive XR and holography*: quantum semantic encoders that reduce bandwidth while preserving perceptual fidelity [85].
- *Secure communications*: QML anomaly detectors safeguarding quantum-augmented FL [86] and blockchain protocols [87].

QML acts as a universal enabler across physical, network, and application domains, focusing on sustainability and trust. Fig. 2 depicts the structured connectivity of QML for 6G networks.

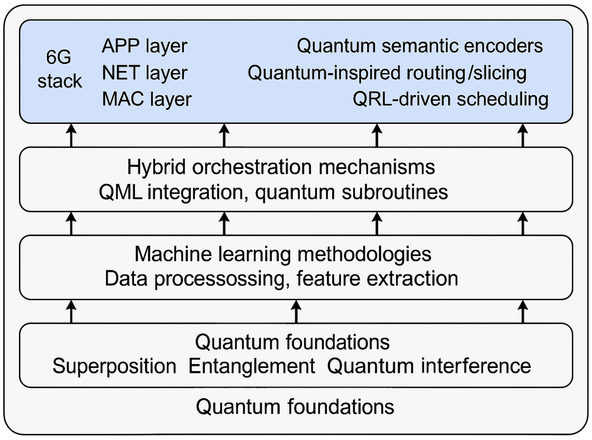

Figure 2. The fundamentals of QML layers and connectivity

3. Taxonomy of QML Methods for 6G

QML encompasses a broad spectrum of models and methodologies that integrate quantum computing principles into classical learning paradigms, offering transformative capabilities for next-generation 6G networks [88]. By leveraging fundamental quantum properties such as superposition, entanglement, and parallelism, QML provides avenues for overcoming the scalability, latency, and complexity bottlenecks inherent in classical approaches. This section presents a detailed taxonomy of QML methods tailored for 6G applications, categorized based on learning paradigms, network stack layers, core models, quantum-inspired approaches, hybrid frameworks, and emerging research directions [89]. The taxonomy highlights not only the algorithmic dimensions but also their role in supporting ultra-reliable, low-latency, energy-efficient, and semantically intelligent communication systems envisioned in 6G. Fig. 3 illustrates QML distribution for 6G.

3.1. Learning Paradigm-Based Classification

QML methods are fundamentally organized by the quantum principles they exploit. Each paradigm provides distinct advantages for enhancing learning efficiency, representational capacity, and adaptability to dynamic 6G environments.

Quantum Superposition. A qubit can exist in a combination of the basis states using Dirac's bra-ket notation $|0\rangle$ and $|1\rangle$ simultaneously, enabling the encoding

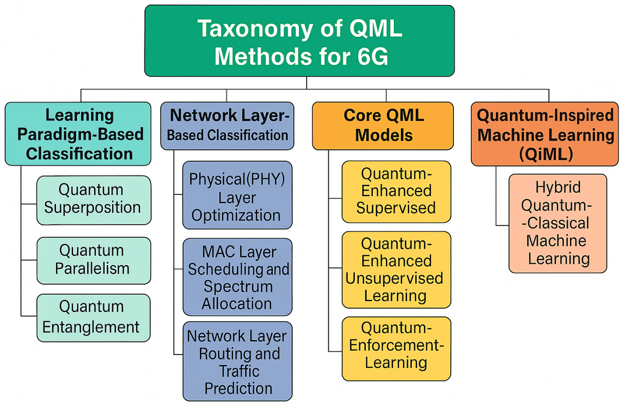

Figure 3. Taxonomy of the QML in 6G network

of multiple possibilities in parallel. This parallelism accelerates learning tasks such as joint multi-user signal detection, semantic-aware feature extraction, and multi-resource allocation optimization [85, 90]. For instance, in vehicular networks where signals overlap in dense environments, superposition allows quantum-enhanced detection schemes to evaluate several hypothesis simultaneously, leading to faster and more accurate classification.

Quantum Parallelism. By exploiting superposition, quantum systems inherently perform computations across exponentially many states in a single operation. This intrinsic parallelism allows QML algorithms to explore vast solution spaces simultaneously, making them highly effective for combinatorial optimization and reinforcement learning [91]. Applications include anomaly detection in ultra-dense IoT deployments, predictive caching in content distribution networks, and rapid reconfiguration of UAV flight paths in SAGIN scenarios.

Quantum Entanglement. Entangled qubits exhibit non-local correlations such that the state of one qubit directly influences the other, even across long distances. Entanglement underpins distributed quantum learning architectures where correlated data can be processed synchronously across edge, aerial, and satellite nodes [83]. For 6G, entanglement facilitates secure cooperative learning among heterogeneous devices, synchronized optimization in federated quantum networks, and resilient communication under adversarial conditions.

3.2. Network Layer-Based Classification

QML can be systematically mapped onto the 6G network stack, offering cross-layer intelligence for end-to-end optimization.

PHY Layer Optimization. Quantum-enhanced algorithms target key physical-layer challenges such as ultra-massive MIMO, THz and visible-light communications, and channel estimation in high-mobility environments [85]. The QAOA supports beamforming design under power constraints, while QSVMs improve signal classification in noisy channels. Quantum-assisted error correction further reduces bit error rates, ensuring robust physical-level reliability.

MAC Layer Scheduling and Spectrum Allocation. At the MAC layer, QRL agents dynamically allocate spectrum resources, reducing collisions in dense IoT and vehicular environments [88]. Quantum kernels facilitate sub-millisecond spectral occupancy analysis, while quantum clustering ensures equitable resource distribution in mMTC deployments. Such adaptability enables efficient handling of bursty traffic patterns and ensures QoS in ultra-low-latency applications like telesurgery or autonomous driving.

Network Layer Routing and Traffic Prediction. Quantum-enhanced routing algorithms integrate QAOA with latency- and energy-aware constraints, identifying optimal paths in SAGIN and UAV mesh networks [92]. Quantum regression improves traffic forecasting, enabling proactive congestion management. Meanwhile, quantum clustering supports adaptive handover and load balancing, essential for ensuring seamless connectivity in highly dynamic vehicular and aerial networks.

3.3. Core QML Models

QML redefines conventional learning models by embedding them in quantum frameworks, yielding superior generalization, scalability, and efficiency.

Quantum-Enhanced Supervised Learning. QSVMs and Quantum Neural Networks (QNNs) map classical data into high-dimensional Hilbert spaces, improving separability of overlapping signals and enhancing generalization [93]. Use cases include modulation recognition, interference classification, network intrusion detection, and fault prediction in critical infrastructure networks.

Quantum-Enhanced Unsupervised Learning. Quantum clustering (Q-Means), Quantum Principal Component Analysis (QPCA), and Quantum generative models reveal hidden patterns in unlabeled data [94]. These methods are effective for unsupervised spectrum sensing, adaptive user grouping in dense networks, and mobility profiling in vehicular environments. Quantum generative models also hold promise for synthetic dataset generation, addressing data scarcity in rare-event detection.

Quantum-Enhanced Reinforcement Learning (QRL). QRL integrates PQCs into reinforcement learning frameworks, enabling exploration of exponentially large action spaces [95]. Hybrid actor-critic designs accelerate

UAV trajectory optimization, adaptive network slicing, and cooperative resource orchestration in SAGIN. The quantum-enhanced policy search also improves robustness against dynamic channel conditions and adversarial threats.

3.4. Quantum-Inspired Machine Learning (QiML)

QiML methods imitate quantum principles but operate on classical hardware, offering near-quantum benefits without quantum devices [96]. Techniques such as amplitude encoding, entanglement-inspired correlation modeling, and tensor-network approaches enhance optimization and dimensionality reduction. QiML is particularly suitable for 6G edge devices with limited computational power [83, 90]. It enables applications such as mobility prediction, lightweight clustering for IoT nodes, and heuristic-driven scheduling for real-time decision-making.

Hybrid Quantum – Classical Machine Learning. Given the limitations of NISQ devices, hybrid QML frameworks provide a practical pathway by combining quantum modules with classical deep learning systems [80]. PQCs serve as quantum feature encoders, while classical layers handle large-scale optimization. Examples include:

- Quantum-classical Generative Adversarial Networks (GANs) for holographic media and XR content generation [97].
- Hybrid autoencoders for semantic compression in intent-based communication.
- Federated Quantum Learning (FQL) for privacy-preserving collaborative training across IoT and edge networks [98].

Such integration balances scalability with quantum advantage, ensuring deployability in near-term 6G systems. Table 4 gives the overview of the comparative analysis of the QML models in 6G networks.

4. Cross-Domain Architectures in QML for 6G

6G networks operate across diverse environments, like terrestrial, aerial, spaceborne, vehicular, nanoscale, and immersive, requiring seamless coordination between distinct domains [99, 100]. These domains differ in latency, reliability, trust, energy constraints, and communication protocols. Classical AI methods lack the scalability and unified abstraction to optimize across such heterogeneity. QML, leveraging entanglement, superposition, and quantum-enhanced optimization, enables integrated intelligence across these domains [101]. This section presents the foundational components of QML-based cross-domain architectures for 6G and summarizes in table 5.

4.1. Federated Quantum Learning (FQL) Across Domains

FQL offers a privacy-preserving, decentralized approach to train QML models across multi-domain 6G infrastructures.

- *Quantum Circuit Training at the Edge*: Network edge devices (e.g., UAVs, vehicles, IoT gateways) locally train Variational Quantum Circuits (VQCs) on domain-specific data [102]. These circuits are lightweight, noise-resistant, and need minimal quantum hardware.
- *Entangled Model Aggregation*: Quantum entanglement directly captures correlations between local models in the quantum state, enabling faster convergence, consensus, and knowledge transfer across non-IID (non-identical and independent) data domains [103].
- *Privacy and Communication Efficiency*: QML models exchange quantum-encoded gradients or compressed embeddings to maintain privacy and minimize bandwidth [104]. Quantum teleportation and dense coding reduce communication costs in diverse networks.

4.2. Quantum Embedding of Domain-Specific Features

QML enables domain-agnostic learning through quantum feature embedding, allowing distinct domains to be processed in a shared Hilbert space.

- *Quantum Feature Maps for Heterogeneous Data*: Quantum feature maps embed classical inputs from different domains into high-dimensional quantum states [105]. This enables unified pattern learning while preserving local characteristics.
- *Cross-Domain Kernel Transferability*: Quantum kernel methods enable domain-transferable similarity metrics, facilitating meta-learning and rapid adaptation [106]. For instance, a kernel trained on UAV mobility data can enhance vehicular trajectory prediction.
- *Semantic-Preserving Representations*: QML-based encoders maintain data semantics across domains, facilitating joint optimization and cross-modal fusion [107].

4.3. Entangled Control Plane for Cross-Layer Synchronization

Real-time cross-layer decisions are needed despite delays and topology shifts. QML ensures rapid coordination with entangled control signaling.

Table 4. Comparison of QiML, Hybrid Quantum–Classical ML, and QML for 6G Networks

Aspect	QiML (Classical)	Hybrid Quantum–Classical	QML (Quantum-Forward)
Hardware	CPUs/GPUs/NPUs	Classical + QPU (cloud/on-prem)	QPU-centric
Latency predictability	High	Medium (queue/shots)	Variable (hardware dependent)
Maturity (TRL)	High	Medium	Low → Medium (task-specific)
Typical 6G role	Near-RT RIC, edge loops	Non-RT analytics, near-RT with shallow PQCs	Non-RT tuning; targeted near-RT when feasible
Example tasks	Scheduling heuristics, clustering, anomaly detection	Kernel lifts, policy search, RIS tuning	QSVM/QAOA for decoding/scheduling, QRL
Main risks	Limited upside on some tasks	Barren plateaus, shot noise	Integration + proving real advantage
Strength	Deployable now, energy-efficient	Practical NISQ path, measurable gains	Potential step-change on hard combinatorics

- *Distributed Entangled Controllers*: Control qubits shared among domain-specific Software-Defined Networking (SDN)/Network Function Virtualization (NFV) controllers enable instant updates across them via entanglement [107]. This ensures synchronized resource allocation and fault recovery.

- *Quantum Teleportation for State Propagation*: Quantum teleportation allows real-time transfer of control states across domains without physical transmission, perfect for dynamic and mobile networks [108].

- *Resilient Control in Dynamic Environments*: In mobile or degraded domains like UAV swarms and emergency networks, QML-based control planes predict failures and synchronize reconfigurations using quantum correlation [109].

4.4. Trust and Security in Cross-Domain QML Architectures

Cross-domain architectures function in semi-trusted or adversarial settings, while QML integrates security and trust into learning and decision-making.

- *Quantum Bayesian Trust Models*: QML integrates quantum-enhanced Bayesian inference to reason over uncertain trust scores. These models are probabilistic, adaptive, and suitable for noisy and dynamic domains [110].

- *Quantum-Resilient Anomaly Detection*: Quantum autoencoders and Boltzmann machines identify anomalies like poisoned data and side-channel attacks by learning low-energy representations of normal behavior.

- *Trust-Aware Resource Allocation*: QRL uses trust coefficients to modify the reward signal, enabling secure routing, offloading, and orchestration while maintaining performance [111].

4.5. Quantum Cognitive Twin for Domain Federation

A Quantum Cognitive Twin (QCT) serves as a real-time, unified model of all network domains, enabling predictive coordination and global intelligence [112].

- *Quantum Twin State Synchronization*: QML synchronizes digital twins into a global quantum state. It captures inter-dependencies like latency-energy trade-offs or vehicular mobility affecting satellite backhaul [111].

- *Predictive Optimization and Forecasting*: QCT uses quantum temporal models (e.g., Quantum Long Short-Term Memory (QLSTM), quantum Kalman filters) to forecast cross-domain bottlenecks and initiate proactive mitigation [48].

- *Domain Interaction Simulation*: QCT simulates scenarios like UAV link failure during vehicular congestion and suggests cross-layer adjustments [113].

4.6. Multi-Domain Resource Allocation via QML

Optimizing bandwidth and power allocation across domains is complex, but QML enables scalable dynamic optimization [114].

- *Quantum Approximate Optimization Algorithm (QAOA)*: QAOA maps cross-domain resource allocation to a quantum cost Hamiltonian, facilitating near-optimal solutions with fewer iterations [107].
- *Variational Multi-Objective Learning*: VQE and hybrid QML models optimize multiple objectives like delay, carbon emissions, and reliability [115]. QML enhances solution diversity by escaping local minima.
- *Domain-Constrained Optimization Policies*: Domains impose constraints: latency for URLLC, carbon for green computing, trust for IoT [116]. QML policies adhere to these while maximizing utility.

4.7. Quantum Graph-Based Interoperability Modeling

Quantum-enhanced graph representations model cross-domain interoperability to reveal network dependencies.

- *Quantum Graph Encoding*: Nodes (e.g., domains, functions, services) and edges (e.g., control flows, data exchange, trust) are encoded in quantum graphs via unitary operations for compact representation [117].
- *Quantum Walk-Based Dependency Discovery*: Quantum walks reveal dependencies, loops, and bottlenecks vital for protocols with tightly integrated operations, such as IoT, UAV, and edge computing [118].
- *Graph Spectral Learning for Protocol Optimization*: QML conducts spectral analysis on quantum graphs to optimize inter-domain protocol translation, cross-layer scheduling, and path selection amid complex dependencies [119].

5. Emerging QML Technologies for 6G

5.1. Hybrid Quantum–Classical Neural Architectures

Hybrid quantum–classical neural architectures integrate variational quantum circuits with classical networks to explore complex solutions using superposition and GPU-based training [116]. Embedding quantum feature maps and gates into deep learning enhances data representation with fewer parameters and adjusts circuit depth for expressivity and decoherence balance [120]. Co-processing with quantum hardware and GPUs allows fast prototyping, while error mitigation and circuit optimization address qubit constraints. This synergy accelerates convergence and advances high-dimensional feature extraction in 6G signal processing.

5.2. Quantum Kernel Methods for Ultra-Fast Pattern Recognition

Quantum kernel methods leverage Hilbert space's dimensionality by encoding radio features into quantum states, allowing rapid similarity evaluations beyond classical kernels [121]. Adaptive quantum kernels dynamically adjust entanglement patterns based on real-time channels, enhancing class separability for tasks like signal classification. This results in faster kernel computations and improved pattern recognition under 6G's low-latency needs. As quantum hardware advances, these methods offer near-instant decisions across high-frequency bands.

5.3. Quantum Reinforcement Learning for Dynamic Resource Management

QRL uses parameterized quantum circuits to optimize spectrum sharing and network slicing rapidly [122]. For quick beamforming control, quantum agents adjust antenna patterns to enhance link reliability and spectral efficiency amid changing network conditions. By integrating quantum-encoded semantic representations, reward functions can more closely match user experience metrics [123]. This combination of QRL and semantic awareness revolutionizes balancing resource use with user satisfaction in 6G networks.

5.4. Quantum Generative Models for Channel Emulation and Anomaly Detection

Quantum generative models like Quantum Generative Adversarial Networks (QGANs) and Boltzmann machines are key for creating high-quality THz channel simulations and modeling traffic patterns in dense URLLC networks [124]. QGANs independently generate authentic channel profiles for 6G transceivers, minimizing over-the-air measurement needs, while Boltzmann machines identify anomalies, including hardware issues and security threats, with minimal false alarms. These models capture intricate correlations in network data, allowing quick communication parameter adjustments and proactive fault detection [115]. This paves the way for robust, self-optimizing 6G networks with predictive maintenance.

5.5. Adversarial Defense Mechanisms in QML-Enabled Networks

Adversarial defense in QML-powered 6G networks addresses threats such as quantum kernel poisoning, circuit backdoors, and adversarial qubit noise [125]. This is achieved through solutions like quantum-safe cryptographic model authentication, adversarial training for circuit hardening, and gradient masking for sensitivity protection. These strategies strengthen

Table 5. QML Architectures for Cross-Domain 6G Systems

Architectural Pillar	Quantum Techniques and Mechanisms	Cross-Domain 6G Applications
Decentralized Quantum Edge Intelligence	Variational quantum circuits (VQCs), entangled model updates, federated quantum averaging	Scalable, private learning across internet of vehicles (IoV), UAV, and IoT nodes with minimal communication
Unified Quantum Feature Representation	Domain-adaptive quantum kernels, high-dimensional Hilbert embedding, hybrid encoders	Anomaly detection, predictive analytics, and transfer learning across NTN, Internet of BioNanoThings, and edge networks
Entangled Control Synchronization	Teleportation of control states, entangled software-defined networking (SDN) signaling, distributed qubit consensus	Instant coordination of controllers in mobile backhaul, UAV mesh, and hybrid radio access networks (RANs)
Quantum Trust and Resilience Layer	Quantum Bayesian inference, quantum Boltzmann machines, trust-aware QRL	Secure routing, reliable task offloading in mixed-trust multi-operator domains
Global Quantum Cognitive Twin	QLSTM-based forecasting, quantum twin fusion, system-wide unitary modeling	Real-time system-level prediction and proactive orchestration across digital twin layers
Cross-Layer Quantum Resource Allocation	QAOA, VQE, Hamiltonian optimization under domain constraints	Multi-resource scheduling across terrestrial, satellite, and edge nodes
Quantum Graph Interoperability Mapping	Quantum walks, spectral Quantum Graph Neural Networks (QGNNs), unitary graph embeddings	Protocol harmonization and dependency discovery across heterogeneous domains

QML pipelines against both data-driven and hardware attacks, ensuring network performance under targeted threats [126].

5.6. Quantum Semantic Communications

Quantum semantic communication shifts from traditional bit-focused methods by encoding meaning in entangled quantum states, reducing redundancy and improving reliability in fading conditions [122]. Quantum-enhanced decoders use machine reasoning in Hilbert space to recover semantic content despite data loss, ensuring message fidelity amid channel issues. This enables applications like real-time holographic telepresence with semantic guarantees for immersive experiences over busy 6G links [127]. By focusing on meaning rather than raw data, it paves the way for intelligent, context-aware connectivity.

5.7. Enabling the Quantum Hardware Ecosystem

The 6G quantum hardware ecosystem includes photonic quantum processors with room-temperature operation and high-bandwidth optical I/O, integrating seamlessly with optical infrastructure [128]. Long-range quantum repeaters and entanglement routers secure quantum links across metropolitan backbones, facilitating QKD and distributed QML model exchanges at scale. Meanwhile, trapped-ion arrays and superconducting qubit lattices, optimized for low-latency, equip edge data centers for real-time quantum analytics [129]. This diverse hardware foundation supports robust, high-throughput quantum services in next-gen networks.

6. Application Domains of QML in 6G Networks

The convergence of QML and 6G wireless networks marks a pivotal moment with the potential to unlock unprecedented capabilities in telecommunications [130]. As networks move toward ultra-low latency, massive connectivity, and intelligent operations, QML emerges as a transformative enabler that can address the exponential growth in complexity across layers [131]. This section explores the multifaceted application areas where QML can reshape 6G architectures and performance.

6.1. Quantum-Enhanced Physical Layer

Advanced Signal Processing Through Quantum Algorithms. The 6G physical layer encounters challenges with THz frequencies, massive antennas, cell-free setups, and complex propagation [132]. QML offers quantum techniques using superposition and entanglement for potential computational gains over classical methods.

- *Quantum MIMO Detection Systems*: Traditional massive MIMO detection becomes computationally demanding with more antennas and higher modulation. QML presents algorithms such as QAOA and VQE for efficient maximum-likelihood detection, reducing search complexity and runtime with parallel methods [133]. QNNs adapts detection patterns to real-time Channel State Information (CSI) and variable propagation.

- *Quantum Channel Estimation and Prediction*: Accurate THz channel estimation is crucial in dynamic settings. Quantum kernel methods enhance denoising and estimation by mapping features into high-dimensional spaces [134]. Quantum recurrent architectures capture temporal correlations in time-varying channels, aiding predictive CSI tasks like proactive scheduling, interference reduction, and beam tracking [135].

- *Quantum-Assisted Beamforming*: Control and holographic beamforming produce complex combinatorial spaces. Quantum annealing rapidly optimizes phase configurations for thousands of elements, enhancing spatial resolution and interference suppression with low latency, even with mobility and blockage [136].

6.2. Intelligent Resource Management

Quantum-Driven Network Intelligence. 6G must manage spectrum, power, compute, storage, and spatial resources to meet varied service requirements. QML supports scalable adaptive and predictive resource management [137].

- *QRL for Spectrum Management*: Spectrum allocation in sub-6 GHz, millimeter-wave (mmWave), and THz bands presents a complex challenge [138]. QRL uses quantum parallelism to efficiently explore large action spaces, finding policies that enhance spectral efficiency, reduce interference, and maintain URLLC constraints [139].

- *Dynamic Network Slicing Optimization*: Network slicing requires real-time allocation of resources across eMBB, URLLC, and mMTC [140]. QML employs variational quantum optimization for resource assignment, maintaining isolation, fairness, and energy efficiency, while adjusting configurations dynamically based on traffic and mobility as per SLAs [141].

- *Quantum-Powered Edge Orchestration*: Near the edge, QML leverages quantum processing units (QPUs) to optimize workload placement and migration [142]. They do this to meet near-RT deadlines, factoring in coherence windows, shot budgets, and communication overheads [143].

6.3. Security and Privacy in 6G

Quantum-Resilient Network Defense. With 6G permeating critical infrastructure, security and privacy must be indispensable objectives. QML augments both classical defenses and quantum-era protections.

- *Post-Quantum Cryptographic Integration*: QML assists in tuning parameters for lattice- and code-based post-quantum cryptosystems and supports quantum-resistant key generation [144]. Learning-driven adaptivity aligns cryptographic profiles with threat levels and performance targets.

- *Quantum-Enhanced Anomaly Detection*: Classical detectors struggle with high-dimensional, heterogeneous telemetry. QSVMs and quantum autoencoders detect subtle deviations indicating faults or intrusions [145]. Emerging quantum homomorphic processing aims to analyze encrypted data while maintaining privacy.

- *Quantum Key Distribution (QKD) Integration*: 6G backbones may include QKD links, with QML optimizing QKD routing, key management, and scheduling by predicting link quality and switching to backup channels when needed [146].

- *Quantum Privacy-Preserving Federated Learning.* Quantum-aware FL uses quantum secret sharing and privacy-preserving aggregation [147], to collaboratively train models, safeguarding local data across operators and domains.

6.4. Semantic and Holographic Communications

Quantum-Enabled Intelligent Information Exchange. 6G is shifting from bit-pipes to meaning-centric communication. QML offers tools to extract, compress, and transport semantic content efficiently [145, 148].

- *Quantum Semantic Encoding and Decoding*: Quantum semantic encoders identify relevant content and compress it for meaning transmission [149]. Quantum natural language processing (QNLP) interprets context and intent, allowing protocols to adjust fidelity based on task importance and channel conditions [148].

- *Quantum-Assisted Immersive Media Processing*: Holographic telepresence and XR need real-time 3D visual and haptic processing [150]. QML methods help improve compression and reconstruction quality, addressing latency and bandwidth challenges.

- *Intent-Based Network Control*: QNLP models translate user intent into network actions, automating configuration to ensure resources meet desired outcomes, beyond just throughput [151].

- *Quantum-Enhanced Brain–Computer Interfaces.* Research in QML for decoding neural signals aims to create fast, intent-driven interfaces potentially integrated with 6G for assistive, medical, or industrial use [82].

6.5. Autonomous Network Operation

Self-Organizing Quantum-Powered Networks. To address 6G's dynamics, networks need to be self-configuring, self-optimizing, and self-healing; QML is central to this autonomy [152]:

- *Quantum Self-Optimizing Networks*: Multi-objective quantum optimizers balance spectral efficiency, energy, latency, reliability, and carbon intensity. QRL and meta-learning enable rapid policy updates under mobility, blockage, and bursty loads [153].
- *Autonomous UAV/NTN Orchestration*: In SAGIN, QRL coordinates UAV trajectories, inter-satellite handovers, and load-aware routing across domains [154]. Quantum swarm intelligence supports large-scale cooperative behaviors for emergency response and dynamic coverage [155].
- *Predictive Network Maintenance*: Quantum time-series models mine telemetry for precursors to failure, enabling preemptive maintenance that minimizes downtime and operational cost [156].
- *Quantum Digital Twins*: Quantum-accelerated simulation pipelines create digital twins of radio and network slices for fast what-if analysis, safe policy rehearsal, and robust change management [157].

7. Challenges and Open Research Issues

The promise of QML for 6G is substantial [118, 158], yet realizing it requires overcoming hardware, algorithmic, integration, and governance hurdles.

7.1. Hardware Limitations and Quantum Error Correction

NISQ Constraints and Scalability. Current NISQ hardware offers limited qubits, short coherence times, and non-negligible gate errors, constraining circuit depth and algorithm duration [159].

- *Quantum Hardware Maturation Timeline*: Qubit systems typically have coherence times from microseconds to milliseconds and gate error rates [160]. Large tasks, like massive joint detection with hundreds of antennas, exceed current reliable processing depths.
- *Error-Correction Overheads*: Fault tolerance remains far off: thousands of physical qubits per logical qubit are often required [161]. Noise-aware ansätze, error mitigation, and variational hybrids tailored to telecom workloads offer pragmatic near-term paths.
- *Hybrid Algorithm Development*: Identify 6G sub-problems where modest-depth quantum subroutines provide net benefit (e.g., constrained combinatorics, kernel lifts) within end-to-end latency budgets [162, 163].
- *Distributed Quantum Computing*: Linking multiple QPUs via quantum networking could scale logical problem sizes; orchestration must account for entanglement distribution, decoherence, and queueing [164].

7.2. Dataset Encoding and Feature Mapping Bottlenecks

Bridging Classical and Quantum Representations. Encoding classical data into quantum states can dominate cost and negate advantage if not engineered carefully.

- *Encoding Complexity*: Basis encoding is qubit-hungry; amplitude encoding is qubit-efficient but requires complex state preparation [165]; angle encoding trades fidelity for shallower depth. Choice impacts robustness and throughput.
- *High-Dimensional, Heterogeneous Data*: 6G data (CSI, mobility traces, traffic matrices) is multi-modal and non-stationary [166]. Encoding must preserve salient structure without exceeding noise-limited depths.
- *Semantic-First Encoding*: Leverage semantic communication to encode only decision-critical features [167]. Quantum autoencoders can learn compact, task-aligned embeddings to reduce redundancy and improve interpretability.
- *Temporal Quantum Feature Maps*: Quantum recurrent and memory-inspired encodings target time-series structure, improving prediction for fast-fading channels and traffic bursts [168, 169].

7.3. Interfacing Quantum Models with Classical Network Protocols

Seamless Integration Across Layers. QML outputs must translate into protocol-compliant actions across PHY/MAC/NET stacks without violating tight deadlines [170].

- *Protocol Layer Integration*: Beam patterns from quantum optimizers must map to RF coefficients; quantum routing decisions must yield standard-compliant forwarding entries.
- *Real-Time Interfaces*: Quantum-classical bridges require deterministic sub-ms latency, emphasizing shallow circuits and precompiled policies for near-real-time controllers URLLC.

- *Standardized APIs*: Common, vendor-agnostic APIs for QPU invocation and result marshaling are needed, with graceful fallbacks when quantum resources are unavailable.
- *Quantum-Aware Orchestration*: Schedulers that co-optimize classical and quantum compute, considering shot budgets, queue delay, and carbon intensity, will enable predictable service [169].

7.4. Security and Trust in Quantum–Classical Hybrid Systems

Comprehensive Security Frameworks. New attack surfaces emerge at quantum–classical boundaries and in cloud-executed quantum jobs.

- *Hybrid Vulnerabilities*: Risks include data leakage during encoding/decoding, side channels on QPUs, and model extraction via query analysis [161]. Defense-in-depth must span both domains.
- *Quantum Adversarial ML*: Adversaries may craft perturbations in quantum state space or exploit decoherence [171]. Robust, certifiable QML and detection of quantum-domain adversarial activity are open problems [172].
- *Federated Quantum Learning Security*: FQL must resist poisoned updates and preserve privacy during aggregation across heterogeneous nodes [173].
- *Trust Management*: Heterogeneous QPU backends and varied assurances require trust anchors, attestations, and auditing.
- *Quantum-Secured Blockchain*: Combining quantum-resistant signatures with distributed ledgers can underpin tamper-evident control and telemetry in hybrid networks [174].

7.5. Standardization and Regulatory Frameworks

Toward Global Standards for Quantum-Enhanced Networks. Interoperability and accountability require coordinated standards.

- *Multi-Organization Coordination*: Harmonize efforts across ITU-T, 3GPP, IEEE, and quantum standards bodies to avoid fragmentation [175].
- *Quantum Performance Benchmarking*: Define telecom-specific benchmarks, datasets, and metrics that account for probabilistic outcomes, noise, and hybrid execution.
- *Quantum Service-Level Agreements (Q-SLAs)*: Specify latency envelopes, shot budgets, error rates, success probabilities, and fallback behavior for quantum services [176].
- *Regulatory Frameworks*: Address spectrum for quantum links, certification of QKD/PQC systems, and privacy regulations for quantum data flows [176].
- *International Quantum Network Governance*: Develop cross-border agreements for quantum internet protocols, data sovereignty, and coordinated response to quantum-enabled threats.

8. Future Research Directions

8.1. Post-NISQ and Fault-Tolerant QML for 6G

Current QML is limited by NISQ devices, so research should focus on fault-tolerant quantum computing for scalable 6G solutions [177]. Fault-tolerant QML could enable complex quantum networks and learning agents for ultra-massive MIMO, semantic communications, and global traffic engineering [178]. Key areas include designing low-overhead error correction codes, modular architectures, and mapping 6G tasks onto fault-tolerant qubits.

8.2. Quantum Federated Learning for Privacy-Preserving 6G AI

Privacy and data sovereignty are vital in 6G, where federated AI will likely dominate [96]. Advancing QFL is essential for collectively training quantum models without sharing raw data. Challenges include managing non-independent and identically distributed (i.i.d.) data, addressing quantum communication bottlenecks in updates, and integrating QFL with edge computing for ultra-low latency [95]. Combining QFL with post-quantum cryptography and quantum-secured communication enhances privacy-preserving intelligence in 6G.

8.3. Quantum Digital Twins for Network Simulation and Control

Digital twins are key to 6G, enabling real-time network simulation and control. Quantum-enhanced twins promise exponential speedups for simulating complex networks, providing detailed insights into mobility, spectrum, and faults [179]. Research should focus on hybrid twins combining quantum and classical models for improved predictive and proactive decisions in the 6G ecosystem.

8.4. Cross-Layer Quantum Optimization Frameworks

6G needs to balance spectral efficiency, latency, reliability, energy, and security through cross-layer optimization [180, 181]. Future work should develop QML frameworks to optimize PHY parameters, MAC scheduling, and network routing. Quantum algorithms like QAOA and VQE offer scalable solutions. Developing quantum-aware network operating systems to manage quantum subroutines in real time is a promising area [182].

8.5. Ethics, Sustainability, and Societal Impact of QML in 6G

QML in 6G not only brings technical advances but also raises ethical, equitable, and sustainable concerns [183]. Since quantum computing hardware uses significant energy, QML in 6G must meet carbon-neutral goals [184]. Ethical issues focus on transparency, decision accountability, and equal access across regions. Research should focus on sustainable QML designs, ethical AI–quantum governance, and ensuring quantum-enhanced 6G benefits all, avoiding digital divides [185].

9. Conclusion

Quantum Machine Learning (QML) is crucial for 6G networks, overcoming classical intelligence limitations in scalability, latency, adaptability, and sustainability. By applying quantum principles like superposition, entanglement, and parallelism to classical and hybrid frameworks, QML enables intelligent, secure, and eco-friendly 6G systems. This study outlines taxonomy, cross-layer architecture, and research directions, emphasizing QML as essential for the next generation of wireless systems. As quantum hardware and integration evolve, QML will reshape how 6G networks learn and manage complexity.

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